

The Distributional Effect of Fintech Credit: Evidence from E-commerce Platform Lending

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The Rise of Platform Lending

BloombergTechnology

Amazon's Lending Business for Online Merchants Gains Momentum

Amazon's Lending Business for Online Merchants Gains Momentum

By Spencer Soper and Serena Wang
April 7, 2015, 8:00 PM CDT

Online retailer issued \$1 billion in loans on

MONEY 20/20

PayPal has lent more than \$1 billion to small biz

Harriet Taylor | @HarrietT
Published 12:31 PM ET Tue, 27 Oct

CNBC

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Square's Newest Offering: Bank Loans

Loans through a partner bank will be an add-on service to Square's core payments business

By Telis Demer
March 24, 2016 8:00 PM CDT

BloombergTechnology

Ant Financial Consumer Lending Reaches \$95 Billion

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Bloomberg News
March 12, 2016, 3:39 AM CDT (Updated on March 12, 2016, 8:00 PM CDT)

Ant's outstanding consumer loans outstrip China's No. 2 bank

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Research Question

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 - Small firms: < 5 employees, ave. monthly sales \$6,700, ave. credit \$6,000

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- Correlation: at product category level, sales HHI positive corr. with credit
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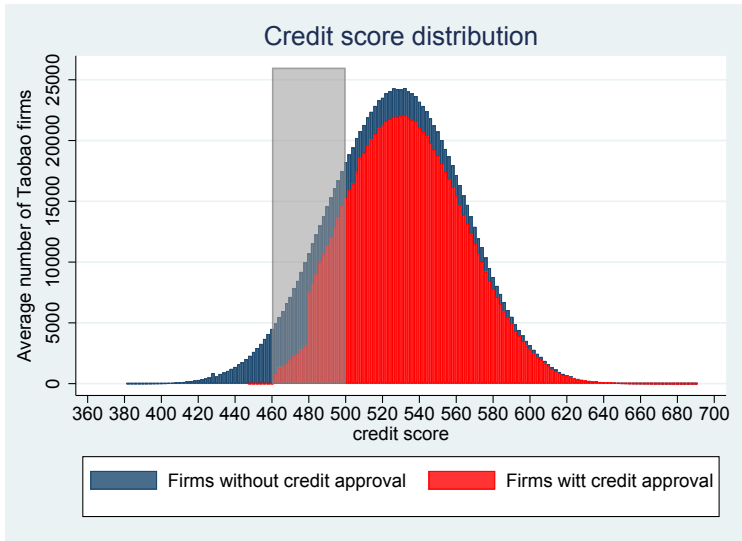
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- Heterogeneity: financial constraint, or investment opportunities?
 - LATE stronger in expanding industries, promotion month (diff-in-diff)

Outline

- Introduction
- **Regression Discontinuity Design**
- Summary Statistics
- Results
- Takeaways

Regression Discontinuity Design – Firm Distribution by Credit Score



- Fuzzy: (1) AF's decision depends on other info; (2) data frequency

Regression Discontinuity Design – Method

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 - 2 LHS = market share, product price etc.
 - Control: industry FE, time FE, firm characteristics (Lee, Lemieux (2008))

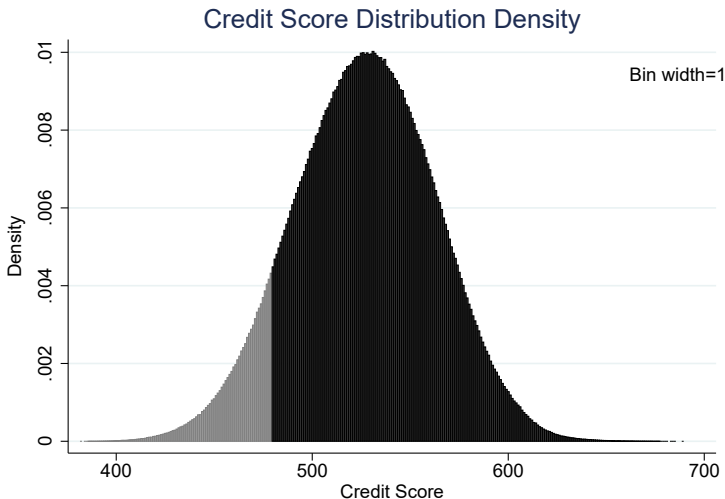
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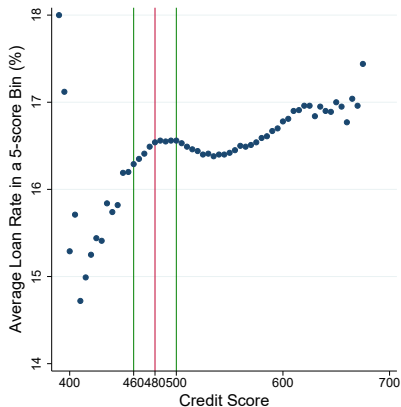
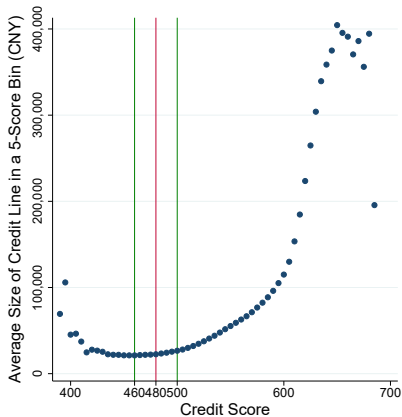
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 - Control: industry FE, time FE, firm characteristics (Lee, Lemieux (2008))
- Heterogeneous effect: lagged sales percentiles, customer rating subsamples
- Sample selection concern: credit is *offered* by AF to merchants
 - 4 types: credit needed (or not), credit obtained (or not)

Regression Discontinuity Design – Smooth Score Distribution

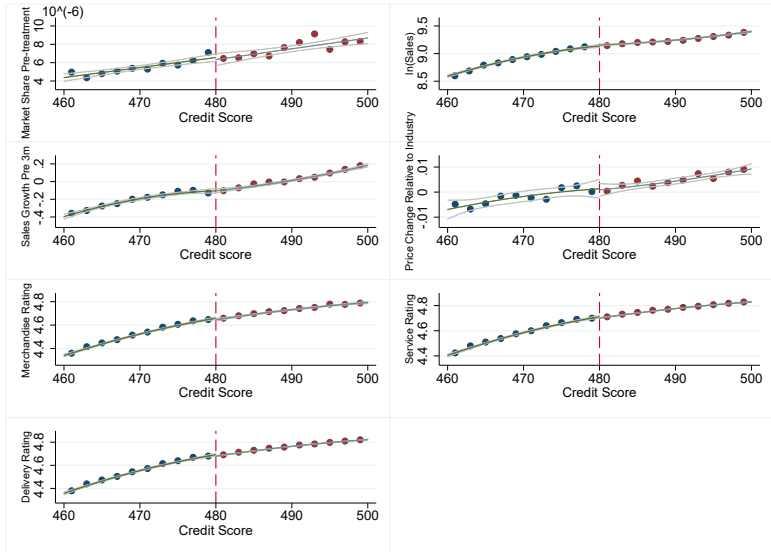


- Can (do) merchants manipulate the score? McCrary (2008)
 - (1) Merchants do not observe their score at all; (2) they do not know AF's credit decision rule; (3) it is impossible to back out the decision algo

Regression Discontinuity Design – Is 480 Designed to be Special?



Regression Discontinuity Design – Smooth Firm Characteristics



- Pre-treatment mkt share, $\ln(\text{sales})$, sales growth, product price, ratings

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Summary Statistics – Total Outstanding Credit Line

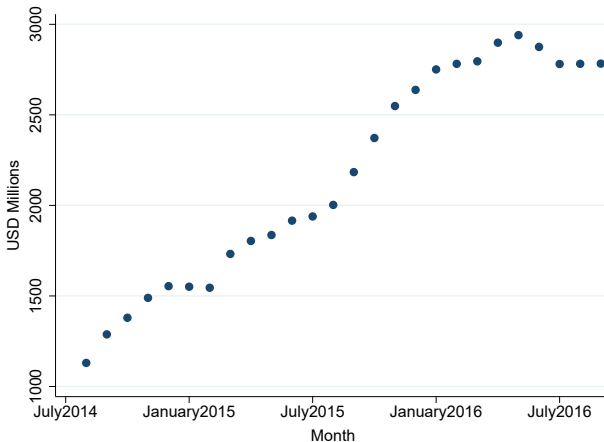
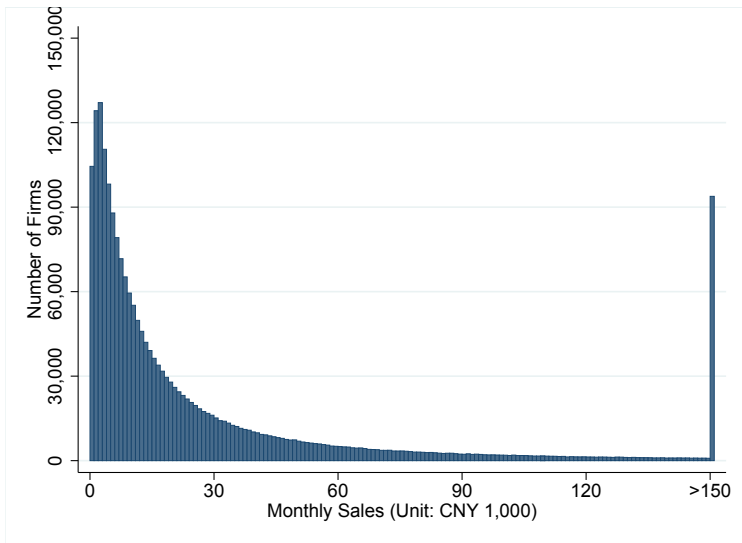


Figure: Total Volume of Credit Lines Outstanding by Month.

Summary Statistics – Merchant Size Distribution



Summary Statistics – Merchant Characteristics

	Observations (1)	Full Sample Mean (2)	STD (3)	Credit Score in [460, 500] Observations (4)	Mean (5)	STD (6)
Panel A: Online credit information						
<i>Credit Approval (0/1)</i>	12, 014, 748	0.775	0.417	1, 146, 740	0.638	0.481
<i>Credit Line, Approval = 1 (CNY)</i>	9, 315, 393	40,879	112, 057	731, 730	25,767	71, 942
<i>Credit Use/ Credit Line, Approval = 1 (CNY)</i>	9, 315, 393	0.144	0.483	731, 730	0.209	0.618
Panel B: Firm characteristics						
<i>Sales (CNY)</i>	12, 014, 696	45,675	195, 970	1, 146, 740	31,944	121, 210
<i>Market share</i>	9, 534, 712	5.654E-5	8.239E-4	1, 146, 740	9.65E-6	1.78E-6
<i>Ln(sales+1)</i>	12, 014, 696	8.894	2.719	1, 146, 740	9.134	1.593
<i>Credit score</i>	11, 970, 625	523	37.35	1, 146, 740	487	16.48
<i>Deliver rating</i>	12, 014, 748	4.495	1.245	1, 146, 740	4.699	0.571
<i>Service rating</i>	12, 014, 748	4.504	1.256	1, 146, 740	4.715	0.586
<i>Merchandise rating</i>	12, 014, 748	4.478	1.241	1, 146, 740	4.669	0.574

- 77.5% firm-month with credit access, 63.8% in RDD sample
- Ave. credit line is CNY 40,879 (approximately \$6,000), close to ave. sales
- Credit usages: 14.4%, and 20.9% in RDD sample
- Market share is extremely small, almost atomic firms

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Results – Motivation

Table: Herfindahl-Hirschman Index (HHI) and Credit Availability

Dependent variable:	HHI		
	(1)	(2)	(3)
Constant	0.0401*** (5.805)	0.0393*** (2.849)	0.0459*** (30.069)
Credit Line / Total Sales	0.0519*** (9.020)	0.0516*** (8.902)	0.0329*** (8.377)
Product Category FE	No	No	Yes
Month FE	No	Yes	Yes
Observations	1,185	1,185	1,185
R^2	0.0684	0.0725	0.3701

Results – RDD First Stage

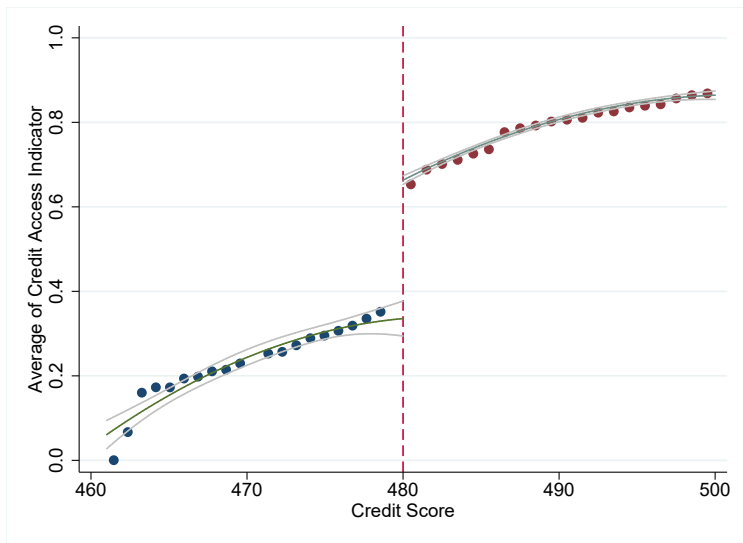


Figure: The Average of Credit Access Indicator in Each 1-point Credit Score Bin.

Results – LATE of Platform Credit on Market Share Change

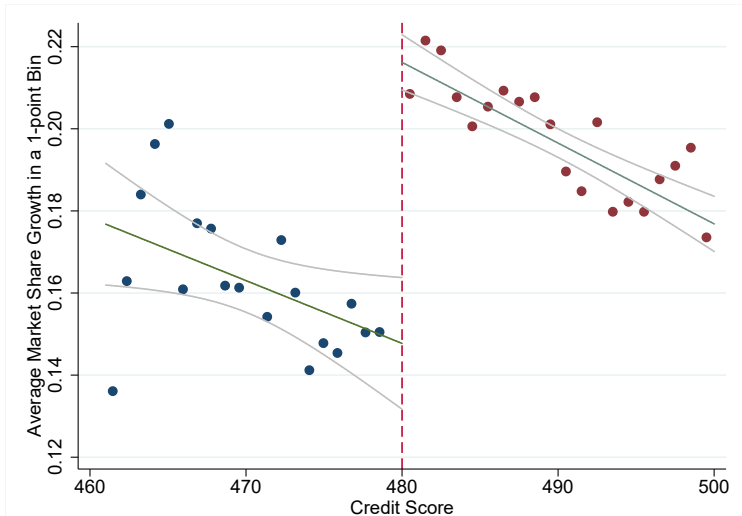


Figure: The Average of Market Share Growth in Each 1-point Credit Score Bin.

$$Y_{firm,t+1} = \Delta \ln (Sale_{firm,t+1}) - \Delta \ln (Sale_{industry,t+1})$$

Results – Platform Credit → Market Share Growth

Dependent variable:	$\Delta \ln(\text{sales}_{\text{firm},t}) - \Delta \ln(\text{sales}_{\text{industry},t})$					
	second stage			first stage		
	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	0.1048 (1.20)	0.1784*** (23.24)	0.0994*** (4.10)	0.3916*** (4.41)	0.4346*** (365.6)	-0.0333*** (-4.717)
Instrumented credit access	0.0612*** (2.68)	0.0512*** (3.83)	0.0741*** (5.59)			
If Creditscore above 480				0.2551*** (122.2)	0.2335** (113.4)	0.2126*** (105.6)
Control variables	No	No	Yes	No	No	Yes
Product Category (Industry) FE	Yes	No	No	Yes	No	No
Month FE	Yes	No	No	Yes	No	No
Product Category \times Month FE	No	Yes	Yes	No	Yes	Yes
Observations	1, 146, 740	1, 146, 740	1, 146, 740	1, 146, 740	1, 146, 740	1, 146, 740
R^2 *	0.012	0.0001	0.0165	0.3174	0.3045	0.3355

* R^2 is overall R^2 for models with separate category and month fixed effects. R^2 is within R^2 for models with interacting fixed effects.

- A merchant outgrows peers by 6.12% once obtains credit (close to graph)

Results – The Distributional Effect of Platform Credit by Size

Dependent variable:		$\Delta \ln(sales_{firm,t}) - \Delta \ln(sales_{industry,t})$								
		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Intercept		0.0275 (0.32)	−0.1218 (−1.39)	0.118 (1.36)	0.0575*** (5.288)	−0.0209 (−1.219)	0.0609*** (3.822)	0.0748*** (3.186)	0.0176 (0.7035)	0.006 (0.2558)
Instrumented credit access		0.0213 (0.73)	−0.0896*** (−2.72)	0.0738** (2.53)	0.0265 (1.102)	−0.051 (−0.1946)	0.2761*** (9.64)	0.0318 (0.918)	0.0012 (0.018)	0.003 (0.0618)
100× Mkt share percentile	(×10 ^{−3})	0.515** (2.5)			1.905*** (9.58)			−0.7456** (−2.3)		
100× Mkt share percentile × IV credit access	(×10 ^{−3})	4.107*** (19.14)			2.299*** (10.5)			4.792*** (19.97)		
ln (sales+1)	(×10 ^{−3})		8.931*** (31.24)			−18.39*** (−5.997)			−33.75*** (−9.81)	
ln (sales+1) × IV credit access	(×10 ^{−3})		57.46*** (20.85)			77.57*** (24.01)			49.69*** (16.83)	
Firm sales growth (Past three-month)	(×10 ^{−3})			53.01*** (41.58)			59.55*** (45.87)			10.86*** (6.504)
Firm sales growth × IV credit access	(×10 ^{−3})			26.70*** (14.14)			19.88*** (10.36)			92.28*** (44.57)
Control variables		No	No	No	No	No	No	Yes	Yes	Yes
Product Category		Yes	Yes	Yes	No	No	No	No	No	No
Month FE		Yes	Yes	Yes	No	No	No	No	No	No
Product × Month FE		No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Observations		1, 146, 740	1, 146, 740	1, 146, 740	1, 146, 740	1, 146, 740	1, 146, 740	1, 146, 740	1, 146, 740	1, 146, 740
R ² *		0.0186	0.0175	0.0247	0.0069	0.0063	0.0144	0.0169	0.0162	0.0179

* R² is overall R² for models with separate category and month fixed effects. R² is within R² for models with interacting fixed effects.

- 4.1% ↑ in lagged mkt share if one decile higher
- 1.1% ↑ if the lagged sales increase by 20%
- 0.5% ↑ if 20% increase in past-quarter growth rate

Results – The Distributional Effect of Platform Credit by Customer Ratings

Dependent variable:	$\Delta \ln(sales_{firm,t}) - \Delta \ln(sales_{industry,t})$								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Intercept	-0.0852 (-0.9731)	-0.0778 (-0.8889)	-0.0767 (-0.9119)	0.3588*** (25.85)	-0.0494*** (-3.599)	0.1703*** (15.45)	0.0263 (1.057)	0.0346 (1.42)	0.0304 (1.228)
Instrumented credit access	-0.0607 (-1.133)	-0.0686 (-1.256)	-0.0712 (-1.294)	-2.706*** (-52.0)	-0.0088 (-0.1654)	-3.306*** (-61.14)	-0.0011 (-0.0189)	-0.0040 (-0.0680)	-0.0016 (-0.0266)
Merchandise rating ($\times 10^{-3}$)	-26.83*** (-7.685)			-19.86*** (-5.465)			46.53*** (5.652)		
Merchandise rating × IV credit access	0.167*** (20.32)			0.5516*** (69.83)			0.1723*** (18.72)		
Service rating ($\times 10^{-3}$)		-34.01*** (-10.03)			-55.91*** (-15.88)			-58.41*** (-7.63)	
Service rating × IV credit access		0.1732*** (20.53)			0.1995*** (24.46)			0.1759*** (19.11)	
Delivery rating ($\times 10^{-3}$)			-40.16*** (-11.54)			41.16*** (10.16)			-28.13*** (-3.405)
Delivery rating × IV credit access			0.1861*** (22.03)			0.635*** (79.45)			0.1641*** (17.44)
Control variables	No	No	No	No	No	No	Yes	Yes	Yes
Product Category	Yes	Yes	Yes	No	No	No	No	No	No
Month FE	Yes	Yes	Yes	No	No	No	No	No	No
Product × Month FE	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
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R ² *	0.0144	0.014	0.0143	0.0058	0.0028	0.0067	0.0172	0.0171	0.017

* R² is overall R² for models with separate category and month fixed effects. R² is within R² for models with interacting fixed effects.

- 16.70% ↑ if merchandise rating ↑ 1; 17.32% ↑ if service rating ↑ 1;
18.61% ↑ if delivery rating ↑ 1

Results – Credit Transmission Channel

- Cross-section heterogeneity → the distributional effect of platform credit
 - Investment opportunity: reputable firms face stronger product demand
 - Financial constraint: smaller and less cash-rich firms are more constrained
 - ▶ Credit has bigger impact on smaller firms, those with less cash flow

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 - Financial constraint: expanding product demand → cash flow, so weaker credit impact (e.g., Chevalier, Scharfstein 1996; Campello 2006)
 - ▶ Weaker credit effect if positive product demand shock

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 - ▶ Weaker credit effect if positive product demand shock
 - Investment opportunity: expanding product demand → capture customers
 - ▶ Customer switching cost: Klemperer (1987), Farrell, Shapiro (1988)
 - ▶ Customer attention is scarce: Dinerstein, Einav, Levin, Sundaresan (2018)
 - ▶ Stronger credit effect if positive product demand shock

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 - ▶ Credit has bigger impact on smaller firms, those with less cash flow
- A time-series perspective on investment vs. financial constraint
 - Financial constraint: expanding product demand → cash flow, so weaker credit impact (e.g., Chevalier, Scharfstein 1996; Campello 2006)
 - ▶ Weaker credit effect if positive product demand shock
 - Investment opportunity: expanding product demand → capture customers
 - ▶ Customer switching cost: Klemperer (1987), Farrell, Shapiro (1988)
 - ▶ Customer attention is scarce: Dinerstein, Einav, Levin, Sundaresan (2018)
 - ▶ Stronger credit effect if positive product demand shock
- A difference-in-difference setting: Nov (“Singles Day”) vs. other months
 - 11/11, 2017 \$25.3 bn vs. \$11.6 bn on Black Friday + Cyber Monday

Results – Credit Impact Varies with Industry Conditions

Dependent variable:	$\Delta \ln(\text{sales}_{\text{firm},t}) - \Delta \ln(\text{sales}_{\text{industry},t})$					
	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	0.1466* (1.67)	0.0794 (0.91)	0.1461*** (8.936)	0.1462 (0.7602)	0.000769 (0.033)	0.0935*** (4.017)
Instrumented credit access	0.0724** (2.46)	0.0762*** (2.73)	0.076** (2.412)	0.0922 (0.2616)	0.000381 (0.00527)	0.0205 (0.4124)
100 × Industry sales growth percentile (Past three-month) ($\times 10^{-3}$)	-2.327*** (-20.21)					
100 × Industry sales growth percentile × IV credit access ($\times 10^{-3}$)	1.419*** (9.00)		0.7465*** (4.639)		1.969*** (9.245)	
November × IV credit access		0.056*** (4.426)		0.1307*** (4.211)		0.1449*** (11.58)
Control variables	No	No	No	No	Yes	Yes
Product Category	Yes	Yes	No	No	No	No
Month FE	Yes	Yes	No	No	No	No
Product Category × Month FE	No	No	Yes	Yes	Yes	Yes
Observations	1, 146, 740	1, 146, 740	1, 146, 740	1, 146, 740	1, 146, 740	1, 146, 740
R^2 *	0.0112	0.0122	0.0001	0.0002	0.016	0.0167

* R^2 is overall R^2 for models with separate category and month fixed effects. R^2 is within R^2 for models with interacting fixed effects.

- 1.4% ↑ if the past-quarter growth of industry is 1 decile higher
- 5.6% ↑ in promotion month (“Singles Day”)

Results - Competition Structure: Credit → Product Price?

Dependent variable:	$\Delta \ln(\text{productprice}_{\text{firm},t}) - \Delta \ln(\text{productprice}_{\text{industry},t})$					
	Second Stage			First Stage		
	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	0.0349 (0.4329)	0.0010 (0.4845)	0.00000992 (−0.0014)	0.3916*** (4.41)	0.4346*** (365.6)	−0.0333*** (−4.717)
Instrumented credit access ($\times 10^3$)	12.4 (1.673)	0.616 (0.164)	0.00677 (0.00179)			
If Credit score above 480				0.2551*** (122.2)	0.2335*** (113.4)	0.2126*** (105.6)
Control variables	No	No	Yes	No	No	Yes
Product Category	Yes	No	No	Yes	No	No
Month FE	Yes	No	No	Yes	No	No
Product Category \times Month FE	No	Yes	Yes	No	Yes	Yes
Observations	1, 146, 740	1, 146, 740	1, 146, 740	1, 146, 740	1, 146, 740	1, 146, 740
R^2 *	0.0027	0.000105	0.000120	0.3174	0.3045	0.3355

* R^2 is overall R^2 for models with separate category and month fixed effects. R^2 is within R^2 for models with interacting fixed effects.

- Bertrand competition: credit impact on market share through quantity
 - Strategic interaction: credit → product price ↓ (Bolton, Scharfstein 1990)

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 - ▶ Heterogeneous investment opportunities: size, rating – merchant credibility
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- More findings on the information set of platform as lender
 - Credit score increases in size and customer ratings (amplifying effect)
 - Substitutes: proprietary info collection vs. customer info aggregation

Literature

- Fintech credit: Petersen and Rajan (2002) on increasing distance between small businesses and their lenders; Berg, Burg, Ana Gombović, Puri (2018) on alternative data and credit analysis; Buchak, Matvos, Piskorski, Seru (2017) and Fuster, Plosser, Schnabl, Vickery (2018) on mortgage
 - Alibaba data: Hau, Huang, Shan, Sheng (2018) on segmented credit market in China; Huang, Lin, Sheng, Wei (2018) on service quality
- Size distribution under financial constraint: Aghion, Bolton (1997); Matsuyama (2000); Cooley, Quadrini (2001); Albuquerque, Hopenhayn (2004); Clementi, Hopenhayn (2006)
 - Size distribution: Simon, Bonini (1958); Lucas (1978); Evans (1987); Hall (1987); Axtell (2001); Cabral, Mata (2003); Luttmer (2007); Angelini, Generale (2008); Moll (2014); Gabaix (2016)
- IO & finance: Maksimovic (1990); Chevalier (1995); Phillips (1995); Chevalier, Scharfstein (1996); Kovenock, Phillips (1997); Campello (2003, 2006); Fresard (2010)
- Two-sided platform design: Rochet, Tirole (2006) etc.

Appendix I: Product Categories and HHI on Taobao.com

Category name	HHI	Category name	HHI	Category name	HHI
Men Cloth	0.0001	Milk Powder/Food Supplements/Nutritious Snacks	0.001	Takeaway / Delivery / Ordering	0.0127
Women Shoes	0.0001	Large household electronic appliances	0.0011	Gaming: equipments, currency, account, delegate player	0.0134
Women Cloth	0.0001	Books/Magazines/Newspapers	0.0011	Discount hotels and hostels	0.0138
Home Decoration Materials	0.0002	Children's shoes/parent-child shoes	0.0011	Education and training	0.0146
Auto Accessories and Supplies	0.0002	Dietary products	0.0012	Electronic game accessories	0.0148
Hardware Tools	0.0002	Hair Care/Wigs	0.0012	Attractions Tickets / Live Performances / Theme Parks	0.015
Bags leather goods / women handbags / men bag	0.0002	Network equipment/network related	0.0012	Online shop, web service, and software	0.0172
Home decoration products	0.0003	Audio and video appliances	0.0012	Digital products (domestic brands)	0.0181
Home textile products	0.0003	Jewelry / Diamond / Jade / Gold	0.0012	Used goods	0.0182
Men Shoes	0.0003	Sportswear / Casual Wear	0.0013	Mobile number, package, related services	0.0187
Cosmetics	0.0003	Computer hardware, monitors, other accessories	0.0014	Global delegate shopping	0.0205
Women's underwear / Men's underwear / Indoor clothes	0.0003	Motorcycle/Electric Vehicle/Equipment/Accessories	0.0014	Other food and beverage	0.0261
Toys/Cartron	0.0003	Home devices	0.0014	Others	0.0272
Household furniture	0.0003	Maternity and nutrition	0.0014	Supermarket and shopping mall cards	0.0316
Tableware	0.0004	Pet/Pet food and supplies	0.0015	Cake bread and other shopping gift cards	0.0341
Outdoor and travel products	0.0004	Home customization	0.0016	Leisure and entertainment	0.0373
Jewelry / Fashion Jewelry / Fashion accessories	0.0004	Kitchen appliances	0.0017	Family services and insurance	0.042
Office equipments, consumables, and related	0.0005	Bicycle and related equipments	0.0017	Online shop payment/coupon	0.0533
Bed Linings	0.0005	Sports shoes	0.0019	Decoration design / Construction Supervision	0.0762
Electronic dictionary / electronic books / stationery	0.0005	Fish and meat / fresh fruits and vegetables / cooked food	0.0022	Mobile / Unicom / Telecom recharge center	0.1266
Clothing Accessories, belts, hats, scarves	0.0005	Musical instruments	0.0026	Online game card	0.1663
Daily household products	0.0005	Storage consolidation	0.0027	Public service and charity	0.1777
Commercial/office furniture	0.0005	Sports Bags/Outdoor Bags/Accessories	0.0027	Game Item Trading Platform	0.209
Sports/Yoga/Fitness/Sports fan products	0.0005	Cell phone	0.0028	Transportation ticket	0.2637
Tea / coffee / Drink Mixes	0.0006	Household cleaning products	0.0033	Insurance (remittance charges)	0.2746
Nursing Cleanser/Sanitary Napkin/Aromatherapy	0.0006	Wine and spirits	0.0033	Digital reading	0.3427
Flower and gardening	0.0006	Special crafts	0.0033	QQ (instant chat) service related	0.3529
Digital Accessories	0.0007	Laptop	0.0034	Property / Rent / Commission Service	0.3763
Kitchen Appliances	0.0007	Watch	0.004	New / used car	0.4408
Electronic and Electrical	0.0007	Flash card / U disk / storage / mobile hard disk	0.0043	Service market	0.4534
Personal Care / Health / Massage Equipment	0.0007	Food delivery services	0.0043	Crowdfunding	0.5568
Antique/Bills/Paintings/Collections	0.0007	Movies / Shows / Sports Events	0.0046	Taobao Business Number	0.5644
Festive supplies/gifts	0.0007	Digital Camera/SLR Camera/Camera	0.0056	Other service goods	0.5853
Snacks/Nuts/Local food	0.0007	MP3/MP4/iPod/recording pen	0.0066	Asset sale	0.7231
Children's shoes & clothes	0.0007	Local living services	0.0067	Taobao fashion model	0.7252
ZIPPO, Swiss Army Knife / Glasses	0.0008	Brand name machines / Web server	0.0077	Taobao food service coupon	0.8237
Diapers / Nursing / Feeding / Beds	0.0008	Holiday, visa and other travel services	0.0078	Taobao partner business	0.8504
Traditional nourishing products	0.0009	Music / Movies / Audiovisual	0.008		
Grain, oil, rice, noodles, dry goods, spices	0.0009	DIY computer	0.0096		
Perfume/Beauty products	0.001	Adult products / contraception product	0.0096		
Customization/Design Services/DIY	0.001	Photography/camera services	0.0103		
Basic building materials	0.001	Tablet/MID	0.0122		

Results - Competition Structure: Credit → Quantity Sold

Dependent variable:	$\Delta \ln(\text{transaction}_{\text{firm},t}) - \Delta \ln(\text{transaction}_{\text{industry},t})$					
	Second Stage			First Stage		
	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	0.1988 (0.4822)	0.3461*** (31.32)	0.1032*** (2.941)	0.3916*** (4.41)	0.4346*** (365.6)	-0.0333*** (-4.717)
Instrumented credit access	0.1168*** (3.078)	0.0659*** (3.426)	0.082*** (4.279)			
If Creditscore above 480				0.2551*** (122.2)	0.2335*** (113.4)	0.2126*** (105.6)
Control variables	No	No	Yes	No	No	Yes
Product Category	Yes	No	No	Yes	No	No
Month FE	Yes	No	No	Yes	No	No
Product Category × Month FE	No	Yes	Yes	No	Yes	Yes
Observations	1, 146, 740	1, 146, 740	1, 146, 740	1, 146, 740	1, 146, 740	1, 146, 740
R^2 *	0.0128	0.00004008	0.0087	0.3174	0.3045	0.3355

* R^2 is overall R^2 for models with separate category and month fixed effects. R^2 is within R^2 for models with interacting fixed effects.

Credit Impact on Market Share Growth: Placebo Test

Dependent variable:	$\Delta \ln(sales_{firm,t}) - \Delta \ln(sales_{industry,t})$			
	second stage		first stage	
	[440,480]	[480,520]	[440,480]	[480,520]
Intercept	-0.0081 (-0.03)	0.3239 (0.28)	0.0632 (1.06)	0.7218*** (63.80)
Instrumented credit access	-0.1454 (-0.08)	-0.3607 (-0.22)		
If Creditscore above 460			0.0036* (1.75)	
If Creditscore above 500				-0.0012 (-1.40)
Product Category (Industry) FE	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes
Observations	517, 347	2, 145, 939	517, 347	2, 145, 939
R^2	0.0247	0.0197	0.1608	0.1361